A Novel ANN Equalizer to Mitigate Nonlinear Interference in Analog-RoF Mobile Fronthaul

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***Abstract*—We firstly analyze the nonlinearities in the analog radio-over-fiber-based (A-RoF-based) mobile fronthaul (MFH) systems with a multi-user uplink load. The inter-band cross modulations (XM) present in the common fiber channel cause severe inter-user interference. Then, we propose a novel complex-valued multi-level artificial neural network nonlinear equalizer (ANN-NLE) for single carrier frequency division multiple access (SC-FDMA) signal uplink transmissions. The inter-user interference can be mitigated by employing a multi-user ANN-NLE. Finally, we design an experimental testbed comprising a 60-GHz wireless link and an A-RoF link in order to verify the model predictions and thereby demonstrate the ability of the ANN-NLE to overcome the nonlinear intra-band and inter-band XM in the case of simultaneous joint equalizations of all users (multi-point-to-single-point) as well as in the case of individual user equalizations (point-to-point). From the experimental and simulation results, we demonstrate that the ANN-NLE can substantially reduce the inter-user interference and communication bit error.**

***Index Terms*—5G mobile communication, frequency division multiaccess, neural network applications, optical fiber communication.**

I. Introduction

In the newly proposed 5G architecture, the digital baseband processing hardware (baseband unit: BBU) is moved from several isolated base stations to a common centralized station that supports numerous remote radio units (RRUs). In the new radio (NR) architecture, the current consensus declares that there should be two splits for the baseband functions. The first split is between the RRU and the distributed unit (DU); the second split is between the DU and the central unit (CU) [1]. As a result, the mobile fronthaul (MFH) is split into two parts i.e., Fronthaul I and Fronthaul II. In Fronthaul I, Option 8 separates the RF from the PHY layer and enables the centralization of all the processes at the protocol layer levels at the DUs, leading to tight coordination and more efficient resource and traffic management that reduce initial capital expenditures (CAPEX) and subsequent operational expenditures (OPEX) [2]. Analog radio-over-fiber (A-RoF) based MFH is of particular interest because of its high bandwidth efficiency and low latency. However, current A-RoF schemes suffer from the severe nonlinear degradations in the fiber-wireless channels.

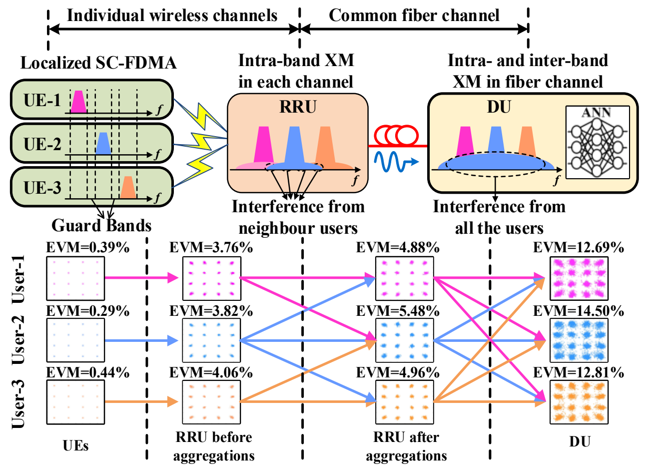

Fig. 1. The A-RoF-based Fronthaul I consisting of three individual wireless channels and one common fiber channel.

The DUs should be able to simultaneously handle the distorted signals from different users and channels, mitigating the nonlinear inter-user interference. The analog MFH relies on A-RoF technology, in which nonlinear transmission impairments can be severe, especially for multi-user signals with high peak-to-average power ratios (PAPR) [3, 4]. The aggregated A-RoF channels simultaneously suffer from fiber and wireless channel nonlinear impairments because at the RRU, the signals are launched directly to air or fiber without any digital processing.

This paper is an extension of our recent work published by OFC 2018 [5]. We introduce, for the first time, a multi-user ANN nonlinear equalizer (ANN-NLE) located at the DU, as shown in Fig. 1. ANN-NLE is used to minimize the nonlinear impediments in A-RoF-based MFH uplink transmissions using single carrier frequency domain multiple access (SC-FDMA) signaling. In this letter, we discuss the overfitting problem and parameter setting of the ANN-NLE. Moreover, the inter-user cross modulation (XM) in a common fiber channel is particularly studied and it cannot be overcome by traditional point-to-point equalization schemes. The proposed ANN-NLE is experimentally demonstrated to mitigate the intra/inter-band

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interferences caused by the nonlinear impairments in multi-user environments.

II. Operating Principle

Fig. 1 shows the Fronthaul I architecture based on A-RoF system with multi-user uplink transmissions. The channel can be separated into two parts: the individual SC-FDMA wireless channels and the common fiber channel. In wireless transmissions, a single-user signal is quasi single-carrier and only suffers from data-dependent intra-band XM between the in-phase (I) and quadrature-phase (Q) components of the vector signals [6, 7]. After transmissions through the wireless channels, the signals from different users are aggregated into one common fiber channel. The strong sidelobes caused by the nonlinearities in wireless channels lead to inter-user interference in multi-user scenarios. This kind of interference can be mitigated by introducing the guard bands between the adjacent channels at the cost of spectral efficiency. The nonlinearity induced by the increasing PAPR in the common fiber link produces nonlinear inter-band XM between users. Inter-band XM between users imposes even more critical signal impairments because one user can interfere with all the other users regardless of carrier frequency positions, a situation that cannot be ameliorated by guard bands, as illustrated at the DU stage in Fig. 1.

With increasing number of users in the common fiber channel, the optical signal is more likely to reach a higher PAPR, leading to nonlinear XM in the common fiber channel. The signals from multiple users are more vulnerable to the nonlinearities due to their higher PAPRs and sidelobe interference.

Fig. 2 shows the structure of a delay tap that is specific to an ANN-NLE with one hidden layer. A sigmoidal function with two saturation regions is the most commonly used activation function in the neuron because of its ability to process small and large signals and because it is readily differentiable. However, in higher order coding applications, such as 16QAM, currently used in SC-FDMA uplink transmissions in 4G LTE, the ANN-NLE architecture with two saturation regions does not lend itself to easy adaptation. As a workable solution, in this paper we employ the previously proposed complex-valued multi-level activation functions for the ANN-NLE in this paper [7]. The input vector $X_i(n)=[x_i(n), x_i(n-1),\ldots, x_i(n-M+1)]^T$ (i=1, 2, 3 and 4) denotes the signals from the i^{th} user. Where $[\cdot]^T$ denotes matrix transposition and M is the tap number for each user and it depends on the system inter-symbol interference (ISI) level. The function $y_{\text{out},i}(n)$ represents the output results of the i^{th} user. Due to the fact that the neurons in the ANN are interconnected with all the other neurons, the proposed ANN-NLE is able to realize joint equalizations with multiple users. The weight values are represented by $w_{k,ij}$, where k represents the weight of the link from the k^{th} layer to $(k+1)^{\text{th}}$ layer, i and j represent the link from neuron i in the former layer to neuron j in the next layer. The neural network is trained by a complex-valued back-propagation algorithm [8].

One of the main problems that may occur in machine learning is referred to as the problem of "overfitting". A good characteristic of a machine learning model is its ability to generalize accurately from the training data to any future data

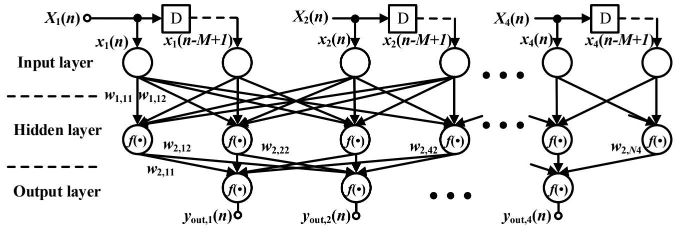

Fig. 2. The structure of delay-tap ANN-NLE with one hidden layer.

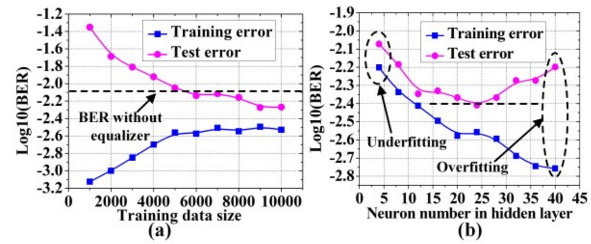

Fig. 3. BER performances of ANN-NLE with 4 users as functions of (a) training data set size of each user and (b) neuron numbers in hidden layer with training and test data set.

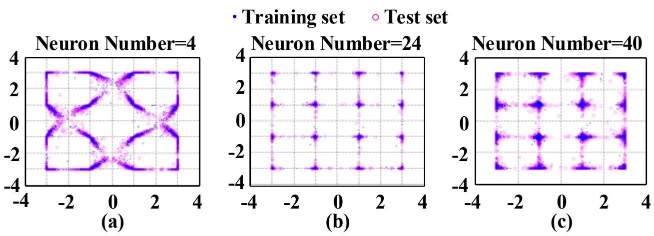

Fig. 4. Constellations of the equalized signals when transmitting 4 users with (a) 4, (b) 24 and (c) 40 neurons in hidden layers.

previously unseen by the model. Over parameterizing the neural network, that is, having a large number of neurons in the hidden layer, can lead to a high probability of "overfitting". The neural network may work well with the training data but exhibit poor performances with previously unseen data with high variance. Fig. 3(a) shows the bit error rate (BER) performances of an ANN-NLE with 4 users as a function of training data set size for each user. The training error grows as a function of the training data set size because the larger the training set, the harder it becomes for the ANN-NLE to fit the training set perfectly. On the other hand, the test error decreases with increasing training data set size. The ANN-NLE reaches its test BER floor when the training data set size is over 10,000 symbols. From Fig. 3(b), we can obtain the optimal scale of ANN-NLE when jointly equalizing 4 users. In the following experiments, the number of neurons in the hidden layer is 24 and the tap number of each user is 5. The training discussed above is offline training and it is completed before applications. Therefore, the latency caused by the offline training can be avoided.

Fig. 4 shows the constellations of the equalized signals in the case of four simultaneously transmitting users jointly equalized with different numbers of neurons in the hidden layer. When the parameters in the ANN-NLE are insufficient, as shown in Fig. 4(a), the constellations of training and test data sets show "high equivalent noise" due to "underfitting". When the neuron number increases to 24 (in Fig. 4(b)), a "low equivalent noise" constellation is produced for both training and test data. The condition of overfitting, in which the ANN-NLE closely follows local data variations, is demonstrated in Fig. 4(c) with 40 neurons in the hidden layer.

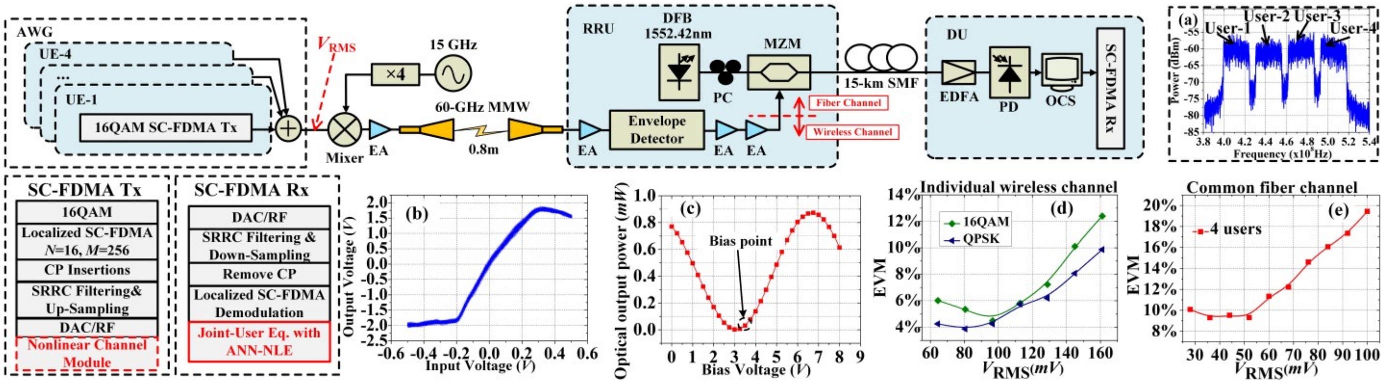

Fig. 5. Experimental setup of the A-RoF-based MFH testbed that uses an ANN-NLE to co-equalize multiple users. Inset (a) is the frequency spectrum of the 4 users at DU. (b) is the measured nonlinear transfer curve of the wireless channel. (c) is the measured transfer curve of MZM, (d) and (e) are the EVMs of the received SC-FDMA signals as functions of V_{RMS} at the output of AWG when suffering from wireless channel nonlinearity and fiber nonlinearity. CP: cyclic prefix, SRRC: square root raised cosine, DFB: distributed feedback laser, PC: polarization controller, MZM: Mach-Zehnder modulator, EA: electrical amplifier, SMF: single mode fiber, EDFA: Erbium doped fiber amplifier, PD: photo detector, OCS: oscilloscope. V_{RMS} is mean square voltage of the intermediate frequency data envelope waveform.

III. Experimental Setup and Results

The proof-of-concept A-RoF MFH testbed, shown in Fig. 5, is composed of user equipment (UEs), RRU and DU. Lacking sufficient RF sources, antennas and amplifiers, the 4-user wireless signals are generated in Matlab, amplified and transmitted by one arbitrary waveform generator (AWG) port through one pair of antennas and amplifiers for simplicity. The N and M in DFT/IDFT and FFT/IFFT are 16 and 256. Four subcarriers are used as guard band spacing. Localized bandwidth allocation SC-FDMA signaling is used, followed by the addition of a 32-point cyclic prefix (CP). Every UE is filtered by a digital square root raised cosine (SRRC) filter with a roll-off factor of 0.2. The additional nonlinear channel module after digital-to-analog converter (DAC)/ radio frequency (RF) in the AWG is used to simulate the individual nonlinear wireless channel of each user. Each channel has its own nonlinear channel module that generates wireless nonlinearity and suffers the nonlinear intra-band XM induced by the simulated channel. The nonlinear module is built up with a sigmoid transfer function which approximates the tested wireless channel as shown in Fig. 5(b). The samples are converted to analog waves by the AWG running at 4 GSa/s. The bitrate and intermediate frequency (IF) are 266.7 Mbps (with 4 users, 66.7 Mbps per user) and 400 MHz bandwidth. A 60-GHz local oscillator (LO) signal and an IF data source from AWG are mixed in a millimeter-wave mixer. The 60-GHz wireless signal is transmitted over a distance of 0.8 m, where the signal is electrically amplified and detected by an envelope detector used for down-conversion from 60 GHz to IF. In this experiment, all components and devices before the Mach-Zehnder modulator (MZM) are designated as the "wireless channel". Then, the remained components are designated as the "fiber channel". The MZM is intentionally operated off its optimal bias point $V_{\pi/2}$ (V_{bias}=3.6 V, V_{π}=3 V) in order to introduce a degree of nonlinearity in the MZM's transfer function to approximate inter-user interference. In practice, the nonlinearities in RRU may be generated in electrical amplifiers (EA), envelope detector or MZM and inter-user XM happens. The electrical spectrum of the received signals from the 4 users are shown in Fig. 5(a). Fig. 5 insets (b) and (c) show the nonlinear transfer curves of the wireless channel and MZM, respectively. Fig. 5(d) shows the nonlinear performances of the wireless channel when transmitting one single user in a SC-FDMA system with QPSK and 16QAM signaling, both of which are commonly used in 4G LTE uplink transmissions. The error vector magnitude (EVM) data in Fig. 5(d) are separately measured into a 50-Ω load, captured by an oscilloscope (OCS) at the end of the wireless channel at RRU. When V_{RMS} is small (V_{RMS}<100 mV), the EVM is dominated by random noise, typical of low signal-to-noise ratio (SNR). With increasing V_{RMS} (V_{RMS}>100 mV), the EVM clearly degrades due to inherent nonlinearities of the mixers, amplifiers and envelope detectors.

Fig. 5(e) shows the EVM behaviors of the signals with 4 users transmitted through the cascaded wireless and fiber channels, indicative of nonlinearities in the fiber channel. EVMs are measured in the case of four simultaneous users while the AWG output, V_{RMS}, is varied within the condition V_{RMS}<100 mV to maintain low nonlinearity in the wireless channel. Combined with Fig. 5(d), when V_{RMS} is larger than 50 mV and smaller than 100 mV, the signals mainly suffer from the nonlinearity in MZM and it causes XM between users.

Fig. 6 shows the measurements under conditions that wireless nonlinearities differs substantially from one user to the next, as determined by the nonlinear wireless channel modules in Matlab (See Fig. 5). Each of the user is distorted in its wireless channel by intra-band XM. The equivalent V_{RMS} in the experimental system for each user are 64 mV, 127 mV, 191 mV and 255 mV, respectively. The nonlinearly distorted signals are then transmitted through the testbed within a relatively small V_{RMS} (65 mV~80 mV) range so as to avoid additional wireless nonlinearities from the mixer at the UE and amplifiers at the RRU in the wireless channel. The MZM is working with V_{bias}=3.6 V to additionally introduce nonlinearities in the common fiber channel, causing inter/intra-band XM. Fig. 6(b)-(e) track how the BER performances of each user vary with IF V_{RMS} signal strengths into the mixer. User-2/3 have relatively worse BER performances than User-1/4 because they are subjected to sidelobe interference from each nearest neighbor in frequency. User-2 has the worst BER because of its lower SNR, which itself is due to the overall channel non-flat frequency response. In order to highlight the advantages of the proposed joint equalization scheme over all users

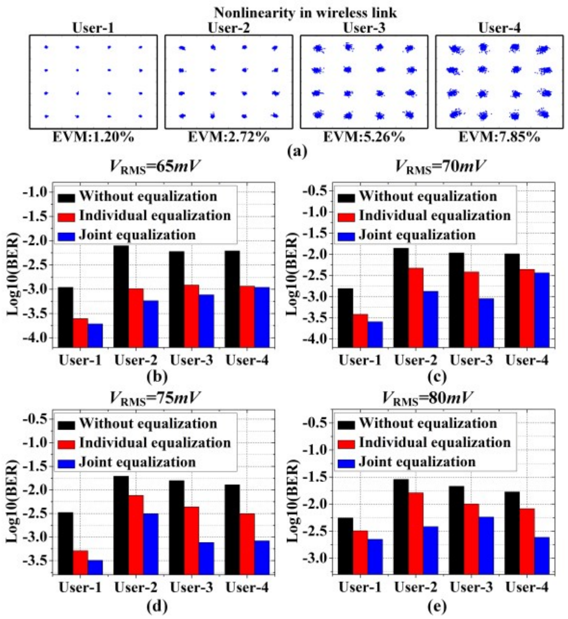

Fig. 6. (a) Constellations of the 4 users with different levels of nonlinearities in their individual wireless channels. (b)-(e) BER performances of the 4 users after transmitted through the fiber-wireless link under different V_{RMS} into the mixer.

simultaneously, first we separate the multi-point-to-single-point transmissions into four point-to-point transmissions and individually equalize every user. In the case of individual equalizations, we use ANN-NLEs with a scale of 5-12-1 and one ANN-NLE for one user. The ANN-NLE has been proven to be better than the traditional equalizers in point-to-point transmissions, such as Volterra-based equalizers [9-11]. As shown in Fig. 3(b), the optimal solution for the joint equalization of 4 users is obtained with an ANN-NLE with a structure 20-24-4 (5 taps for each user at the input layer). When V_{RMS} is in the small value range (65 mV, 70 mV), the advantage of joint equalization is not obvious because of the weak inter-band XM among users. However, when the V_{RMS} increases to 80 mV, the benefits of the ANN-NLE co-equalization method stand out in the presence of stronger inter-user interference. The results show that it is not sufficient to only affect point-to-point channels when mitigating inter-user interference in the A-RoF-based Fronthaul I channel, one must simultaneously equalize all users in both the wireless and fiber channels.

Fig. 7(a) illustrates the BER performances of the ANN-NLE as a function of tap numbers. The tap number is highly dependent on the bandwidths of the signals and the frequency response of fiber-wireless channels. Increasing the tap number can help mitigate ISI. However, continually increasing the tap number leads to the overfitting problem and BER degradations. It can be observed that the optimal tap number with 24 neurons in the hidden layer is 5. Fig. 7(b) shows the mean square error (MSE) of the ANN-NLE with different step sizes η and verifies the tradeoff between the learning rate and the MSE floor.

IV. Conclusions

In this paper, we demonstrate, for the first time, how to design and implement an ANN as a mean to optimize a converged optical and wireless access network. The inter-band XM between users that occurs in the aggregated common fiber channel causes critical inter-user interference and greatly

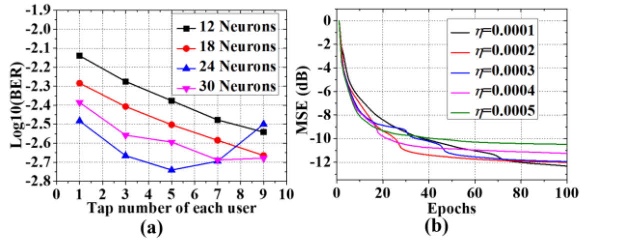

Fig. 7. (a) BER performances of the ANN-NLE as functions of tap numbers with different number neurons in hidden layer. (b) MSE performances of ANN-NLE with different step sizes η.

degrades the signal quality. We have verified that the inter-band interference in the fiber channel from multiple users can be successfully mitigated by the proposed multi-user ANN-NLE. We have demonstrated that conventionally designed point-to-point nonlinear equalizations are unable to mitigate inter-user interference caused by the nonlinear inter-user XM in a common fiber channel. The theoretical analyses and experimental results presented in this paper have proved the validity of our machine learning method for multi-user performance optimization in A-RoF-MFH system.

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